Multi-Temporal Remote Sensing Image-Based Extraction on the Crops Planting Information

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Abstract:

The crop planting information extraction is crucial to the estimation of crop output, the key of which is to speedily and accurately extract planting information through the remote sensing image. The multi-temporal remote sensing data, together with the supervised classification and decision tree classification method, are used in this study to speedily and accurately extract crop planting information from TM/ETM+ remote sensing images and sixteen MODIS time series remote sensing images, to interpret major crops in the Heilonggang area. Overall, classification accuracy is up to 91.3%, compared with one simple supervised classification of TM images. The relative errors of cotton, maize, wheat and vegetables are reduced by 1.3%, 20.5%, 2.0% and 13.8%, respectively. It has been proved that this method has high accuracy and it can serve as an effective index for reflecting the crop planting distribution. The data can provide important scientific basis for the adjustment of the major crop planting structure in the Heilonggang area, and could also provide reference for information extraction in other areas.

Key words:

Remote Sensing; Modis; Evi; Decision Tree Classification; Information Extraction

Introduction

The crop planting structure information covers both the crop types and their spatial distribution. It's of high importance to obtain the crop planting structure information and adjust the structure in time for the sake of local rural economy and the rational utilization of regional agricultural resources (water resources & soil resources). In terms of obtaining the crop planting information, the remote sensing technique is more advantageous and has become widely applied in recent years compared with the traditional time-consuming statistical method which is unable to secure accurate data and explicit spatial distribution information of the crops.

The essence of remote sensing interpretation on planting structure lies in the remote sensing classification, which is designed to differentiate the crop types and monitor spatial distribution of crops and their planting areas by analyzing different spectral characteristics of different crops on the remote sensing images. There is a heap of methods of performing remote sensing classification and the most common one is the supervised and unsupervised classification method. But the cyber-automatic classification method is more suitable for images with low resolution. In recent years, some newly developed methods have emerged, including Artificial Neural Network Classification (ANNC), Support Vector Machine classification (SVM), expert system, decision tree method, fuzzy classification method, etc. It's of vital importance to select appropriate methods for different kinds of data. This study adopts a comprehensive classification method integrating cyber-automatic classification and visual interpretation, supervised classification and decision tree method, multi-data sources and multi-temporal data, which is geared toward securing higher accuracy.

The spatial resolution of Landsat TM images reaches 30 m (except for the infrared wave of the sixth wave band), which can satisfy the requirements of agricultural & silvical investigation, water & land survey, and environmental monitoring, etc. The medium-resolution imaging spectrometer MODIS is able to consecutively provide daylight reflected radiation data and day & night emitted radiation data with high resolution from any places on the earth, including visible light and infrared spectrum data

observed from the land, ocean, and atmosphere. At present, the TM imaging and MODIS method have been widely applied to monitor the growth conditions, acreage, and spatial distribution of such crops as wheat, maize, and cotton. Therefore, by combining the TM/ETM+ image with MODIS data and taking full advantage of high spatial resolution of TM/ETM+ and high temporal resolution of MODIS, this study will monitor and analyze the planting structure and spatial distribution patterns of major crop types in Heilonggang area.

There is abundant research on the remote sensing-based extraction of the crop information, and the NDVI method has been most widely applied, which can reflect the "green degree" of the land cover based on the differences in the land cover's absorption and reflection toward the spectrum with different wave bands. DeFries et al (2000) obtained the global forest coverage density by virtue of AVHRR NDVI information. Cai Xueliang et al (2009) distinguished land-use types in the irrigation areas and extracted the crop structure information by integrating the Landsat ETM+ data and MODIS NDVI data. Yan Huimin et al (2005) divided the crops into three categories: crops with one harvest per year, two harvests per year and three harvests per year. Based on the AVHRR NDVI data, they carried out classification and information extraction on the crops and analyzed their distribution rules. EVI is acquired on the basis of NDVI by adding the atmospheric red light correction parameters, atmospheric blue light correction parameters as well as the soil background adjustment correction parameters, which can eliminate the influence of background environment and the atmospheric noise effectively. This study will adopt 13 time series MODIS EVI images to serve as an auxiliary tool for the TM images in terms of monitoring the crop growth conditions. When studying the fitting relationship between the meteorological elements and the vegetation index variation curve, the semi-automatic identification classification based on fewer field ground survey points needs to be realized by virtue of the decision tree algorithm, which will be a prime orientation for the future research on monitoring large-scale crop distribution. Since the Heilonggang area has a wide-range and large-scale of crop distribution, this study will adopt an integrated method combining the eco-classification-based supervised classification and the decision tree classification method, aiming to secure higher classification accuracy.

Introduction to the Research Area

The Heilonggang area (114°20′- 117°48′E, 38°44′-36°03′) is located in the west of Bohai Sea and in the north of Huang-huai-hai Plain, with the annual average temperature of 11.7-13.3 ℃ and perennial average precipitation of 509 mm. The land area amounts to 34,000 km^2, accounting for 18% of the total land area of Hebei Province. The Heilonggang area has abundant crop types, including wheat, maize, cotton, peanut, pepper, cabbage, tomato, pear, and peach, etc.

Data and Data Pretreatment

Acquiring Data Source

The data used in this study belong to the spring and autumn TM/ETM+ data, especially in 2009, in the Heilonggang area (Table 1). On March 12th, 2011, we downloaded 13 images of MOD13Q1 vegetation index from April, 2009 to October, 2009, which got numbered based on the time series (Table 2). The field data adopt the field investigation data obtained by GPS in May, 2010.

TABLE 1 TM/ETM+ IMAGE DATA LIST IN HEILONGGANG AREA

Orbit No.	Spring Time Phase	Data Type	Cloud/%	Acquisition method	Orbit No	Autumn Time Phase	Data Type	Cloud/ %	Acquisition Method
122033	2009.5.2	Landsat-7ETM+	0	download	122033	2009.8.30	Landsat-5TM	0	download
122034	2008.4.29	Landsat-7ETM+	0	download	122034	2009.8.30	Landsat-5TM	0	purchase
123033	2009.5.17	Landsat-5TM	0	purchase	123033	2009.9.22	Landsat-5TM	0	purchase
123034	2007.5.12	Landsat-5TM	0	download	123034	2009.9.22	Landsat-5TM	0	purchase
123035	2007.5.4	Landsat-7ETM+	0	download	123035	2009.9.22	Landsat-5TM	0	purchase
124034	2007.5.19	Landsat-5TM	0	download	124034	2009.9.13	Landsat-5TM	27	download
124035	2007.5.19	Landsat-5TM	0	download	124035	2010.8.15	Landsat-5TM	26	download

Note：1.the data downloaded come from international scientific data platform of CAS (http://datamirror.csdb.cn)
2. Landsat-7ETM+ is the data obtained after the strip is repaired

TABLE 2 CORRESPONDENCE BETWEEN BANDS OF TIME SERIES AND THE ORIGINAL IMAGES

Time series wave No	1	2	3	4	5	6	7	8	9	10	11	12	13
Original image Days	97	113	129	145	161	177	193	209	225	241	257	273	289

Data Pretreatment

The pretreatment procedure of TM/ETM+ data includes geometric correction, histogram matching, image mosaic, image cutting, band combination, and principle component transformation, while the pretreatment procedure of MODIS data includes format conversion, projection alteration, image cutting, and EVI numerical range transformation. The domain of vegetation index should be [-1, 1], while the original domain of MODIS EVI is [-10000, 10000]. Therefore, the numerical range transformation needs to be conducted. The pixel value of all images should be divided by 10000 by dint of MODELER in the ERDAS 9.2, thus changing the numerical range into [-1, 1].

Methodology

Introduction to Methodology

The pretreated spring and autumn TM/ETM+ images undergo eco-classification-based supervised classification respectively and then the optimal observation time is obtained by analyzing the MODIS EVI curve. With the MODIS EVI time series being the constraint, the classification results should be shifted and corrected through decision tree classification-based artificial intervention. Finally the precision evaluation should be performed on the classification results.

Enhanced Vegetation Index

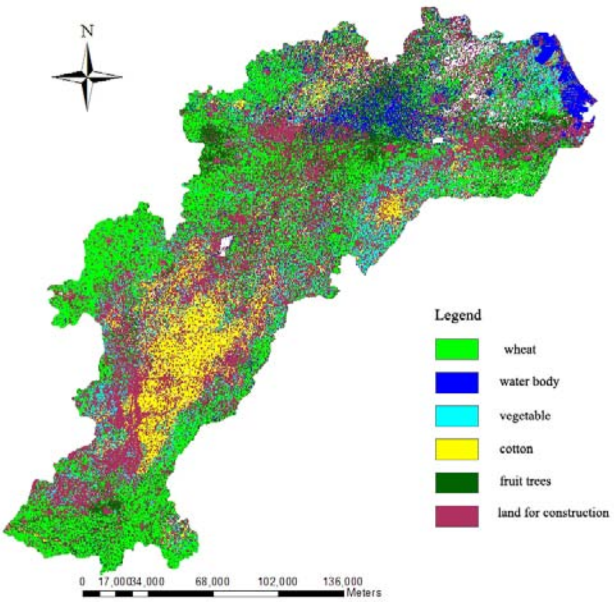
The enhanced vegetation index (EVI) adopts the synthetic method of BRDF/CV-MVC, which can eliminate the influence of atmospheric noise and guarantee an optimal pixel. The calculation is as follows:

$$\mathrm{EVI} = (1+L) \times \frac{\rho_{\mathrm{nir}} - \rho_{\mathrm{red}}}{\mathrm{L} + \rho_{\mathrm{nir}} + C_1\rho_{\mathrm{red}} - C_2\rho_{\mathrm{blue}}} \quad (1)$$

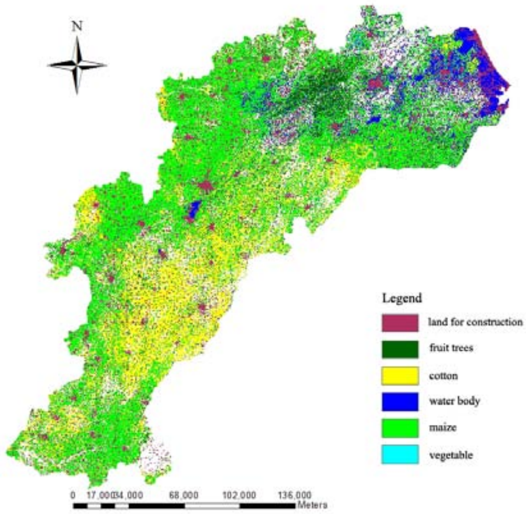
ρ_{nir} stands for the reflectivity of near infrared wave band. ρ_{red} is for the reflectivity of infrared wave band, and ρ_{blue} is for the reflectivity of the blue light band. C_1 r represents the red light correction parameter of atmospheric correction which is valued as 6, while C_2 is for the blue light correction parameter of atmospheric correction which is valued as 7.5. L stands for the soil background adjustment parameter, which is valued as 1.

Eco-Classification-based Supervised Classification

In order to solve the phenomenon of the same object with different spectrums caused by such factors as region and time phase, this study employs the ecological classification method. The principle component-transformed spring and autumn TM/ETM+ images are classified into four subareas. The supervised classification will be performed on the four subareas respectively and then the classification results will be integrated. There will be a number of image patches in the classification results, which need to be treated through such methods as Clump, Sieve, and Eliminate. The GIS Analysis in ERDAS 9.2 is employed in this study to carry out the cluster analysis and elimination of image patches. The aim of Eliminate method is to simplify the classified images. The final supervised classification results of TM/ETM+ images can be seen in Fig.1.



a. Supervised classification results of TM images in spring



b supervised classification results of tm images in autumn

FIG.1 SUPERVISED CLASSIFICATION RESULTS OF TM IMAGES IN SPRING AND AUTUMN IN HEILONGGANG AREA

Decision Tree-based Auxiliary Interpretation of MODIS EVI Time Series Images

The field GPS points and visual interpretation points are used to acquire the growth rhythm of different crops and determine the corresponding EVI value of the sample point in the MODIS EVI image, thus obtaining the growth curves of the wheat, maize, cotton, vegetables, fruit trees (Fig. 2).

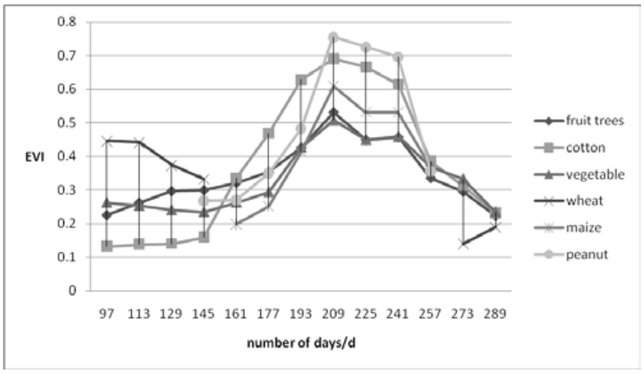
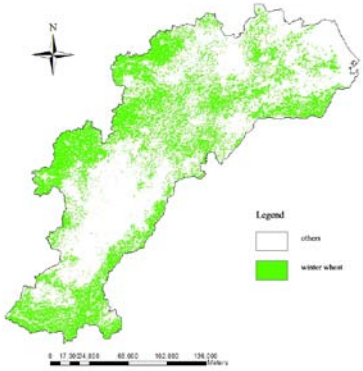


FIG.2 CURVES OF THE MODIS EVI VALUE FOR MAIN CROPS

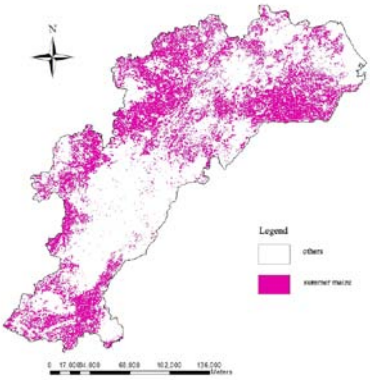
In ERDAS 9.2, thirteen MODIS EVI images can be superposed based on time sequence by virtue of the tool of Interpretater-Utilities-Layer Stack, thus formulating a MODIS EVI time series image containing 13 waves, which can read the MODIS EVI characteristic values corresponding to different interpretation points (Fig.3).

TABLE 3 MODIS EVI CHARACTERISTIC VALUES OF DIFFERENT CROPS IN HEILONGGANG AREA

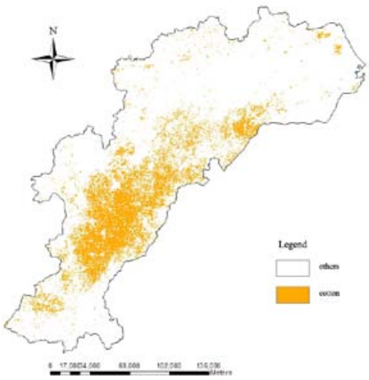
MODIS EVI series wave No	time	1	2	3	4	5	6	7	8	9	10	11	12	13
Fruit trees	Average	0.225	0.262	0.296	0.299	0.321	0.353	0.425	0.532	0.449	0.457	0.335	0.294	0.223
	Max	0.356	0.428	0.424	0.446	0.455	0.479	0.562	0.717	0.668	0.561	0.428	0.374	0.344
	Min	0.111	0.158	0.184	0.185	0.153	0.186	0.287	0.314	0.303	0.303	0.232	0.169	0.128
Cotton	Average	0.131	0.139	0.139	0.160	0.335	0.469	0.628	0.692	0.666	0.615	0.385	0.312	0.232
	Max	0.331	0.395	0.243	0.261	0.409	0.596	0.738	0.807	0.796	0.735	0.466	0.407	0.297
	Min	0.082	0.081	0.098	0.106	0.172	0.197	0.344	0.461	0.367	0.390	0.260	0.201	0.131
Vegetables	average	0.263	0.253	0.240	0.235	0.263	0.293	0.427	0.508	0.450	0.459	0.370	0.333	0.235
	Max	0.454	0.338	0.320	0.335	0.389	0.384	0.575	0.671	0.629	0.610	0.502	0.508	0.493
	Min	0.153	0.154	0.143	0.161	0.159	0.194	0.300	0.359	0.271	0.327	0.244	0.140	0.143
Wheat	Average	0.446	0.441	0.373	0.332	0.211	0.270	0.439	0.638	0.537	0.549	0.383	0.189	0.139
	Max	0.675	0.628	0.517	0.482	—	—	—	—	—	—	—	0.408	0.234
	Min	0.203	0.183	0.160	0.179	—	—	—	—	—	—	—	0.073	0.075
Maize	Average	0.411	0.380	0.324	0.298	0.198	0.252	0.414	0.610	0.532	0.532	0.370	0.233	0.145
	Max	—	—	—	—	0.269	0.414	0.595	0.722	0.657	0.636	0.411	—	—
	Min	—	—	—	—	0.133	0.182	0.286	0.427	0.400	0.374	0.240	—	—
Peanut	Average	—	—	—	0.253	0.298	0.366	0.517	0.784	0.683	0.656	0.208	—	—
	Max	—	—	—	0.268	0.342	0.405	0.585	0.839	0.726	0.697	0.257	—	—
	Min	—	—	—	0.237	0.271	0.342	0.483	0.755	0.631	0.615	0.128	—	—



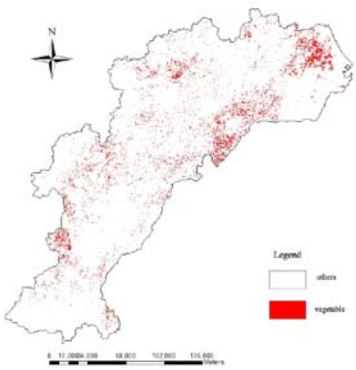
a. winter wheat



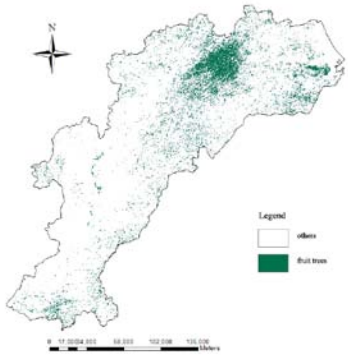
b. summer maize



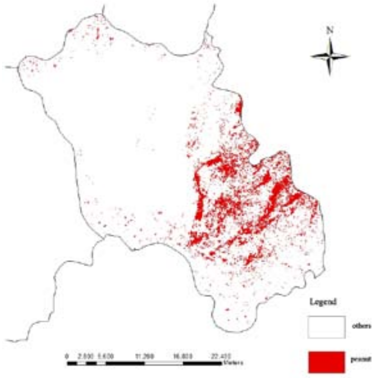
c. cotton



d. vegetable



e fruit trees



f. peanut

FIG.3 INTERPRETATION OF WHEAT, COTTON, MAIZE, VEGETABLES, FRUITS AND PEANUTS IN HEILONGGANG AREA

The minimum value of a certain category is usually taken as the valve value for the EVI characteristic value corresponding to interpretation points, which can help obtain most of the similar image elements through sifting and picking out. Based on the EVI curves, EVI characteristic values, and the valve value selection principle of the decision tree identification model, the decision tree classification results of MODIS EVI have been achieved (Table 3).

1) The Decision Tree Identification Model of Winter Wheat

Based on the MODIS EVI curve of the winter wheat in Fig.2, the first and second time phases are the optimal phase of distinguishing winter wheat from other crops, at which the EVI value stays at being the maximal among all crops, and the EVI value begins to rapidly decrease, while the EVI values of other crops are quite stable or on the increase. Since TM images have high spatial resolution and the classification time phase is the optimal time phase for the remote sensing interpretation of winter wheat, we should first comply with the constraints of classification results of TM image. However, there are about 11% of multiple

pixels in the classification results which need to be sloughed off by virtue of MODIS data. Therefore, the identification model of the winter wheat is as follows:

$$\begin{cases} \text{TM(spring)} = \text{winter wheat} \\ \text{EVI}(1) < 0.203 \\ \text{EVI}(1) + \text{EVI}(2) > \text{EVI}(3) + \text{EVI}(4) \end{cases} \qquad (2)$$

TM (spring) represents TM images after the supervised classification treatment. EVI (1), EVI (2), EVI (3) and EVI (4) stand for the EVI values corresponding to the wheat of No.1, 2, 3, 4 on the time series band.

2) The Decision Tree Identification Model of Cotton

Based on the EVI value curve of the cotton in Fig. 2, the EVI value between the 4th and 5th time phase increases abruptly, which can serve as the mark distinguishing the cotton from other crops. Since the TM image extraction of the cotton classification results is not so accurate, the constraints of TM interpretation results shouldn't be completely accepted. Besides, the growth areas of winter wheat and cotton cannot be overlapped. The classification results of winter wheat need to be firstly used as the mask and the cotton information need to be extracted from the non-wheat growth area. The classification model is as follows:

$$\begin{cases} \text{TM(autumn)} = 1 \\ \text{wheat.img} = 0 \end{cases} \quad \text{or} \quad \begin{cases} \text{EVI}(4) < 0.16 \\ \text{EVI}(5) > 0.33 \\ \text{小�.img} = 0 \end{cases} \qquad (3)$$

Wheat.img represents the final result of wheat information extraction, which is a binary image containing 0 (non-wheat growth area) and 1. TM (autumn) stands for the TM image interpretation results in the autumn, and the pixel value represented by cotton is 1. EVI (4) and EVI (5) stand for the EVI values of the cotton corresponding to the time series wave band 4 and 5.

3) The Decision Tree Identification Model of Summer Maize

Based on the EVI value curve of the summer maize in Fig.2, we can see that the 5th and 6th time phases are the time period from seed sowing to the sprouting of the maize, when other crops in their vigorous growth period. The EVI average value is at the lowest level of the crop EVI values. Since there is overlapping between the summer maize and cotton growth seasons, there shouldn't be overlapping in the planting areas between them. The interpretation of summer maize needs to be under the constraint of the cotton planting area. The identification model of summer maize is as follows:

$$\begin{cases} \text{EVI}(5) < 0.26 \\ \text{EVI}(6) < 0.18 \\ \text{EVI}(7) > 0.3 \\ \text{cotton.img} = 0 \\ \text{TM(autumn)} = 0 \end{cases} \qquad (4)$$

The cotton.image stands for the final result of cotton information extraction, which is also a binary image containing 0 (non-cotton growth area) and 1. The pixel value represented by summer maize in the autumn TM image interpretation results is 2. EVI (5), EVI (6), and EVI (7) mean the EVI values of the maize corresponding to the time series wave band 5, 6, and 7.

4) The Decision Tree Identification Models of Vegetables and Fruit Trees

Based on the EVI value curve of the vegetables and fruit trees, it can be seen that the variations of the two kinds of crops in each time phase are quite similar; therefore, it's difficult to distinguish them through the EVI values. It needs to still abide by the constraints of TM classification results. On the spring TM image, there is no overlapping in the distribution space between vegetables & fruit trees and wheat & cotton, while on the autumn TM image, overlapping cannot be found between vegetables & fruit trees and maize and cotton. The vegetables information should be firstly extracted, and then the information extraction of fruit trees needs to subject to the constraints of vegetables information extraction. The identification model of vegetables is as follows:

$$\begin{cases} \text{cotton.img} = 0 \\ \text{summer maize.img} = 0 \\ \text{TM(autumn)} = 5 \end{cases} \; or \; \begin{cases} \text{cotton.img} = 0 \\ \text{winter wheat.img} = 0 \\ \text{TM(spring)} = 7 \end{cases} \qquad (5)$$

The cotton image, winter wheat image, and summer maize image are all the final extraction results, which are the binary images containing 0 (the non-crop planting area) and 1. The pixel value of vegetables on the spring TM image is 7, while the pixel value on the autumn TM image is 5.

The identification model of fruit trees can be obtained by adding the constraints of vegetables planting area to the identification model of vegetables, which is as

follows:

$$\begin{cases} \text{cotton.img} = 0 \\ \text{summer maize.img} = 0 \\ \text{vegetable.img} = 0 \\ \text{TM(autumn)} = 5 \end{cases} \quad or \quad \begin{cases} \text{cotton.img} = 0 \\ \text{winter wheat.img} = 0 \\ \text{vegetable.img} = 0 \\ \text{TM(spring)} = 7 \end{cases} \tag{6}$$

5) *Interpretation Model of Peanut in Daming County*

Since the early growth stage of peanut and cotton needs the plastic film mulching, their spectral characteristics are quite similar and the EVI value variation of the peanut is similar to that of the cotton. Therefore, it's not so effective to employ the EVI values to interpret the peanut information. Due to the mutual exclusion of the peanut with other crops, related constraints need to be carried out in the process of interpreting the peanut information. The interpretation model is as follows:

$$\begin{cases} \text{cotton.img} = 0 \\ \text{summer maize.img} = 0 \\ \text{vegetable.img} = 0 \\ \text{fruit trees.img} = 0 \\ \text{TM(autumn)} = \text{peanut} \end{cases} \quad \text{or} \quad \begin{cases} \text{cotto.img} = 0 \\ \text{winter wheat.img} = 0 \\ \text{vegetable.img} = 0 \\ \text{fruit trees.img} = 0 \\ \text{TM(spring)} = \text{peanut} \end{cases} \tag{7}$$

The cotton image, winter wheat image, summer maize image, vegetables image, and fruit trees image represent the final extraction results of the cotton, winter wheat, summer maize, vegetables and fruit trees, respectively, which are all binary images containing 0 (non-crop planting area) and 1. TM (autumn) and TM (spring) represent the autumn and spring TM/ETM+ images after the treatment of supervised classification.

Results and Analyses

Analyses on Supervised Classification Results

1) *Analyses on Random Point-based Classification Results*

The research objective is focused on the planting structure of the crops; therefore, the evaluation is made only on the classification accuracy of the major crops. ERDAS 9.2 classifier is employed to generate 100 random points to assess the classification accuracy of the spring and autumn TM images (Table 4 and Table 5).

TABLE 4 CLASSIFICATION ACCURACY ASSESSMENT OF TM IMAGES ON RANDOM POINTS IN SPRING

Crop type	Contrastive point	Correct point	Accuracy/%
Winter wheat	66	64	96.97
Vegetables	11	8	72.73
Fruit trees	23	20	86.96

TABLE 5 CLASSIFICATION ACCURACY ASSESSMENT OF TM IMAGES ON RANDOM POINTS IN AUTUMN

Crop type	Contrastive point	Correct point	Accuracy/%
Cotton	28	22	78.57
Maize	58	55	94.83
Vegetables	3	1	33.33
Fruit trees	11	9	81.82

From the Table 4 and Table 5, we can see that the winter wheat on the spring image and the fruit trees & maize on the autumn image have higher classification accuracy. Due to the large planting area of wheat and maize in the Heilonggang area, it's easy to identify them, thus showing higher classification accuracy. The fruit trees also have higher accuracy because of their concentrated distribution. Since the planting of cotton and vegetables is labor-consuming and time-consuming, the planting area of them is comparatively smaller and sparsely distributed, which makes it difficult to identify and cause obvious classification leakage.

2) *Analyses on Statistics-based Classification Results*

By comparing the crops areas data extracted through TM supervised classification with the areas data obtained in the Hebei Rural Statistic Yearbook (2009), we can obtain the classification accuracy of each kind of crop (Table 6).

Based on Table 6, it can be seen that the effects of TM image interpretation on vegetables and fruit trees are not so satisfactory. The interpretation results are more than 1/4 fewer than the statistical data, and the interpretation result of the maize is 34.26% higher than the statistical data. The interpretation results of cotton and wheat are about 10% higher than the statistical data.

TABLE 6 CLASSIFICATION ACCURACY ASSESSMENT OF TM IMAGES ON STATISTICS

Crop types	cotton	maize	wheat	vegetables	fruit trees
TM interpretation results Pixel/number	6 572 122	14 690 359	13 214 832	2 034 135	3 260 987
TM interpretation results area/hm²	591 490.98	1 322 132.31	1 189 334.88	183 072.15	293 488.83
Yearbook data /hm²	540 214	984 734	1 068 176	245 031	
Relative error/%	9.49	34.26	11.34	-25.29	

Analyses on Auxiliary Interpretation Results

1) Analyses on the Filed Checking Point and Google Earth-based Classification Results

The Google earth images of this area are mostly the SPOT or geoeye images in 2011 with high resolution. The ENVI 4.7 software is employed to load the 100 random points into the Google earth. Related results can be seen in Table 7.

TABLE 7 ACCURACY ASSESSMENT ON DECISION TREE SYSTEM CLASSIFICATION

Crop type	Contrastive point	Correct classification point	Classification accuracy/%
Winter wheat	44	43	97.73
Cotton	27	25	92.59
Summer maize	30	28	93.33
Fruit trees	25	20	80.00
vegetables	12	10	83.33
Total	138	126	91.30

Based on Table 7, we can see that the classification method combining the decision tree-based TM image and MODIS EVI image has high accuracy, with the total classification accuracy reaching 91.3%, while the ISODATA non-supervised classification method and VI curve-based spectral coupling method have a total accuracy of 85.7%. Results indicate that the classification accuracy of winter wheat is the highest, reaching 97.73%. The accuracy of cotton and summer maize can arrive at about 93%, while the accuracy of fruit trees and vegetables is relatively lower, staying at about 80%.

2) Statistical Data-based Accuracy Assessment

By comparing the crops areas data extracted through decision tree-based MODIS EVI classification with the areas data obtained in the Hebei Rural Statistic Yearbook (2009), we can obtain the classification accuracy of each kind of crop (Table 8).

TABLE 8 ACCURACY ASSESSMENT OF DECISION TREE SYSTEM AUXILIARY CLASSIFICATION ON STATISTICS

Crop types	Cotton	Maize	Wheat	Vegetables	Fruit trees
TM interpretation results Pixel /number	5 510 700	12 451 000	12 973 900	2 409 400	3 510 800
Interpretation results area/hm²	495 963	1 120 590	1 167 651	216 846	315 972
Yearbook statistical data/hm²	540 214	984 734	1 068 176	245 031	
Relative error/%	-8.19	13.8	9.31	-11.5	

By comparing Table 6 with Table 8, we can find that the decision tree-based MODIS EVI classification has much higher accuracy than the TM supervised classification. The absolute values of relative error of cotton, maize, wheat, and vegetables decrease by 1.3%, 20.5%, 2.0%, and 13.8%, respectively. Therefore, the classification method combining the decision tree-based TM image and the MODIS EVI image has higher classification accuracy, which can better reflect the crops distribution and serve the purpose of crop classification and extraction more effectively.

Based on the observation of the EVI growth curve lines, it can be seen that the EVI can effectively reflect the crop growth conditions in the period of April-May and July-September. This study adopts the spring TM images in April and May and the autumn ETM+ images in August and September; therefore, the decision tree-based MODIS EVI method in this study has gained satisfactory results, which has a higher accuracy than the MODIS NDVI method employed by Hao Weiping in the previous research. Hence, MODIS EVI is more suitable for serving as the auxiliary interpretation data of TM/ETM+ images than the

MODIS NDVI, which can monitor the crops spatial distribution patterns by reflecting the crops growth conditions.

Conclusions

By taking two episodes of Landsat TM/ETM+ images as the data sources and on the basis of MODIS EVI images and other statistical data, this paper has made interpretations on the crop planting structure conditions in the Heilonggang area by dint of eco-classification-based supervised classification method and successfully extracted the distribution information by virtue of decision tree-based human-computer interaction mode, which can directly reflect the crops spatial distribution and provide scientific basis for the crop structure adjustment.

The classification method combining the decision tree-based TM images and MODIS EVI images can yield much higher classification accuracy with the total accuracy reaching 91.3%. Specifically speaking, the classification accuracy of winter wheat is the highest, reaching 97.73%. The accuracy of cotton and summer maize can hit about 93%, while the accuracy of fruit trees and vegetable is relatively lower, staying at about 80%. The assessment result of statistical data-based interpretation accuracy shows that the absolute values of relative error of cotton, maize, wheat, and vegetables decrease by 1.3%, 20.5%, 2.0%, and 13.8%, respectively, indicating that the combined method can generate higher classification accuracy and can better satisfy the requirements of crops classification & information extraction. Besides, compared with MODIS NDVI, the MODIS EVI is more suitable for serving as the auxiliary interpretation data for the TM/ETM+ images, which can monitor the crops spatial distribution patterns by reflecting the crops growth conditions. Moreover, the focus of future research should be put on the studies of the crop planting structure optimization based on the spatial distribution of water and soil resources.

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